



Chronic Obstructive Pulmonary Disease (COPD) patient's readmission Prediction by using classification models in Machine Learning

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ABSTRACT:

Predicting the Readmission of cases with habitual Obstructive Pulmonary Disease (COPD) using Machine literacy could potentially ameliorate patient issues and reduce healthcare costs. In this paper, we propose to use machine literacy ways to dissect patient data and make a model that can prognosticate the liability of readmission for COPD cases. The three machine literacy algorithms have been applied in the design, videlicet Bracket models like (Artificial Neural Networks (ANNs), Decision Trees (DTs), and Support Vector Machines (SVMs). The data that we will use includes demographic information, medical history, current specifics, and hospitalization history. By relating factors that are associated with an increased threat of readmission, we hope to develop a prophetic model that can be used to ameliorate the operation of COPD and help readmissions. We'll estimate the performance of our model using a dataset of COPD cases that includes information on readmissions. Our thing is to contribute to the development of machine literacy tools that can be used to ameliorate the operation of COPD and reduce the burden of readmissions on the healthcare system.

Keywords –Classification algorithms, COPD readmission, data mining, and decision support system.

1. INTRODUCTION:

Prophetic analytics is one of the most generally used Machine literacy ways in healthcare. Prophetic analytics and data mining have also been employed to control the propagation of habitual conditions. Generally, during the recent decade, healthcare-related exploration has concentrated on developing and enforcing Machine literacy models to address the specific and critical requirements of healthcare systems. Habitual Obstructive Pulmonary Disease (COPD) can be defined as a lung complaint honored by tailwind giving. Worldwide, COPD has been considered one of the major causes leading to

advanced rates of death. The Global Burden of Disease Study estimated 251 million spread cases of COPD in 2016. It was also reported that 3.17 million deaths were caused by COPD in 2015(i.e., 5 of all deaths in that time). The admission rate of COPD cases in the United Kingdom has doubled between 1991 and 2000 and by 2000, reported 1 of all sanitarium admissions.

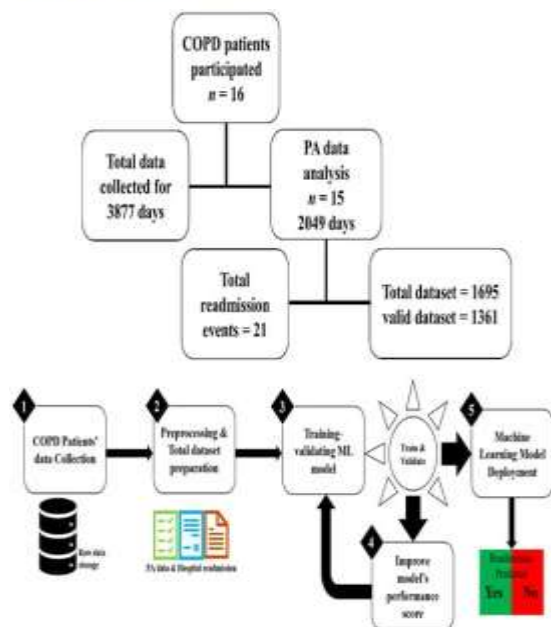


Figure 1. Patient data collection details of COPD

The total costs of lung conditions in the EU (European Union) have been estimated to be about 6 of the total healthcare costs, and COPD was reported as taking the most significant chance (56) of these costs. Readmission is one of the most serious difficulties defying any healthcare system and one of the primary motorists of declining health services. Readmission is defined as admitting cases to the sanitarium within 30 days after being released from the same sanitarium. Hospital readmission is precious for both cases and hospitals (8). As a result, hospitals are working hard to ensure that cases get enough remedy during their first stay in order to reduce the liability of readmission.

2. LITERATURE REVIEW:

Kai Yang: In response to the more noteworthy accessibility of data about clinical benefits, for example, EHR information, an ever-increasing number of ways of taking a gander at this data are being made with the goal that we can gain from it and work fair and square of care. The high intricacy and sparsity of EHR concentrates on present various issues. Rather than different fields, EHR examination techniques should be straightforward and helpful for treatment. Along these lines, preparing in HER demonstrating is required. In this review, we discuss a method for assessing EHRs called Predictive Task

Guided Tensor Decomposition (TaGiTeD). Specifically, TaGiTeD utilizes 3 computerized tensor deterioration to sort out how occasions connect with one another from EHRs in a manner that can be anticipated with high exactness. TaGiTeD might make more exact EHR models than techniques that are not observed. This is significant for most clinical regions on the grounds that independent calculations can't make valuable models from the modest number of patient models they have. By interfacing TaGiTeD with an endorsed EHR data-sharing center, we demonstrate the way that it can make pictures that are both understood and exact.

David Chen: In the space of clinical exploration, individuals are turning out to be more keen on better approaches for felt that can help them assess and coordinate a great deal of information. One of the main objectives is to concentrate on what deep learning means for how a lot of confounded clinical data are utilized. Deep learning is valuable for figuring out the astounding information in electronic health records (EHRs), but because of its limits, it probably won't be appropriate for clinical purposes. With the assistance of time-sensitive observational examinations, we give a short outline of the issues with profound figuring out how to support study into better ways of treating ailments.

Kumari Deepika: Chronic diseases are currently the main source of death all over the planet. Thus, as a preventive step, medical services are putting increasingly more accentuation on every individual's well-being. Be that as it may, making and utilizing an assumption model for constant sicknesses is a major step in the right direction in how clinical consideration is based on data examination and direction. In this review, evaluations of the probability of getting a persistent sickness were made utilizing data from past well-being records. Diabetes and coronary illness were remembered to profit from classifiers like Naive Bayes, Decision Tree, Support Vector Machine (SVM), and Artificial Neural Network (ANN). For this assessment, the achievement pace of activity was estimated by recalling a comparative assessment of various calculations.



Israa Mohamed: In this piece, a confidential occasion diversion plan for spreading emergency division administrations at a confidential Egyptian place in Zigzag is shown. We make a patient stream split model by taking care of patients of how significant they are. Despite the fact that there is a ton of proof that patient division and coordinating work is based on clinical consideration in conditions of standby times and length of stay (LoS), there has been no decent framework assessment or execution of this arrangement. In view of how the structure was seen and how clinical consideration laborers discussed it, an unmistakable and complete image of the system was made that seemed to be a determined model and showed different patient gatherings traveling through the system's pieces. Utilizing the data obtained, a discrete occasion reproduction model of the emergency split is made. To concentrate on the impact of the patient stream split, different valuable circumstances were removed from the case circumstance. These included changing staff capacities and patient numbers. The outcomes show that how the recommended framework is set up might actually cut holding up times and lengths of stay for patients.

Dave Singh: Precision drug is a case- case-concentrated fashion that intends to coordinate all important clinical, heritable, and regular information to acclimate the occasion of incidental goods against the possibility mending for every existent. With respects to individualities with habitual obstructive pulmonary complaint (COPD). In clinical practice, factors like the4 volume of eosinophils in the blood could be employed to more readily target ICS specifics to COPD cases who are deteriorating even though they're taking the perfect proportion of bronchodilators. Considering the ABCD evaluation, the Global Initiative for Chronic Obstructive Lung Disease (GOLD) 2017 drug remedy assessments might be principally the same as the remedy that fair cases first show. In any case, checking during follow-up is more earnestly for individuals who are taking a drug to help them. During follow-up, medicine treatment for COPD will be driven in another fashion. numerous enormous randomized controlled overtures have zeroed in on the salutary issues of

ICSs and long-acting bronchodilators in the treatment of asthma assaults, which has urged a great deal of new information. New data about blood eosinophils and specifics for interior breathing, as well as the need to part beginning and understand the pharmacological idea, impacted the GOLD pharmacological treatment proposition. In this piece, we check out current realities and are behind the GOLD 2019 drug treatment studies.

Joseph Menzin: The managerial cases and qualifying data from a major, multi-state U.S. Federal medical Insurance oversaw care data set were utilized in this Review. Individuals in the review were no less than 65 years of age and had made claims in 2004. The COPD bunch was comprised of individuals who had Something like one ongoing/trauma center case or two short-term claims for COPD that were over 30 days separated (ICD-9-CM codes 491. xx, 492. x, 496). The reference bunch was comprised of individuals without COPD who were a similar age, orientation, month of enlistment, and Government medical care plan as the COPD bunch. The distinction in all-out well-being plan installments between the two gatherings in 2004 was utilized to sort out the additional expenses of COPD. Clinical cases with COPD or other respiratory-related infections and medication claims for respiratory meds were utilized to sort out the costs that were inferable.

3. METHODOLOGY:

Prescient examination is a well-known Machine Learning (ML) technique utilized in the medical services business. For example, and have upheld the utilization of electronic well-being records as the reason for shrewd medical care audits. The development of ongoing sicknesses has likewise been halted with the assistance of conjecture examination and information mining. The latest concentration in the space of clinical benefits has been centered around making and utilizing ML screens that meet the exceptional and significant requirements of clinical benefits frameworks. The majority of these surveys require taking a gander at a great deal of information to figure out more about how the framework functions now and how it will function from now on. Predictive analytics is a common



Machine Learning (ML) tool in the healthcare business. For example, and have argued that electronic health records might be used as a basis for healthcare analysis for smart health. Data mining and predictive analytics have also been utilized by researchers to halt the spread of chronic illnesses. The bulk of recent healthcare-related research has focused on developing and implementing ML models to meet the specific and critical demands of healthcare systems. The bulk of these studies focus on analyzing huge amounts of data to acquire insight into the current and future behavior of the system under study.

4. RELATED WORK

As we mentioned ahead, readmission may be defined as admitting cases to the sanitarium after a short time from their discharge. This short time has been set in the literature to be within 30 to 90 days (11), (12). In this study, we set our readmission time frame to be within 30 days, as typically, healthcare service quality is measured by death rates within 30 days of discharge(13),(14). Hospitals' readmission exploration is generally grounded on variables and data sets for a particular population, patient type, or specific complaint because of the complex data collection procedures needed to get a large quantum of data. still, enough quantum of data has a significant recrimination on the perfection and delicacy of the developed prophetic models. In this study, we're enhancing the generality of the developed prophetic model through a large quantum of data(around 620,000 entries). It occasionally happens that different classes aren't inversely represented which is appertained to in the literature as the class imbalance problem(15). Since most of the conditions aren't generally set up in the whole population, the class imbalance problem may be considered a common problem in the healthcare services field(16). prophetic logical models are largely affected by the class imbalance problem(17). thus, the developed bracket models must take this problem into account and apply some compensation ways. The most generally used compensation ways to balance classes are the different error cost negatives fashion (18), the over-sampling fashion(19), and the under-slice fashion(20). To the stylish of our knowledge, there are limited studies in the literature

that present the problem of imbalanced readmission data(21). Another critical problem that arises when trying to prognosticate sanitarium readmission is the cost imbalance misclassification problem(22). The cost imbalance problem is generally related to the below-mentioned class imbalance problem and hence results in ways in which both problems can enhance each other(15). To the stylish of our knowledge, the readmission prophetic literature has infrequently considered the cost imbalance as a classification problem. Machine literacy algorithms have been extensively used in the literature to classify readmitted cases. utmost generally used algorithms are Logistic Retrogression(LR), Naïve Bayes(NB), Decision Trees(DT), Support Vector Machines(SVM), Artificial Neural Networks(ANN), and Random Forest(RF)(23),(24), and(25). Different studies compared prophetic models grounded on their prognosticated affair(23),(25), and(26). still, the utmost of these studies suffer from poor vaticination quality, as the AUC ranged from 0.57 to 0.74, with only one excepted study of(27), who reported an AUC value of 0.83. So, the low vaticination capability may be added to the challenges of developing prophetic sanitarium readmission models. Although COPD is considered A serious complaint with complicated consequences, it has little attention from experimenters. The available literature studying the threat factors affecting COPD cases ' admission and readmission is rare. On the other hand, numerous studies are fastening on these factors for other classes of cases. For illustration,(28) prognosticated the threat of heart failure cases ' readmission using a multi-layer approach. They examined if cases will ever be readmitted or if they will be readmitted within short(30 days) or long(60 days) readmission time. Naïve Bayes and Support Vector Machine were the applied bracket algorithms in their study. In 2017,(29) prognosticated the threat of heart failure cases ' readmission using the NB bracket algorithm. The loftiest reached delicacy of their model grounded on ACC and AUC was around 85 and 0.77, independently. Reference(30) prognosticated the threat factors of heart failure cases ' readmission grounded on a 30-day time horizon. They applied the LR bracket model and reached a delicacy of 0.78 grounded on the AUC measure. The work done in(



31),(32), and(33) are the rare studies that approached COPD cases. Binsonetal. (31) tried to diagnose COPD, lung cancer, and asthma through the application of an electronic nose, which analyzes mortal exhaled breath and classifies it according to different machine literacy models. Their results achieved high situations of delicacy for the three conditions. Dhar proposed a new ensemble model for the early discovery of COPD(32). The authors espoused 8 classifiers arranged in different pools. An inheritable algorithm has been employed to discover optimal hyperactive- parameters for each classifier. The results of their model outperform utmost of the recent Machine Learning models applied for COPD early discovery. Wu et al.(33) considered the problem of readmission vaticination for COPD cases using a new CORE(COPD – Readmission) score, which predicts a case's readmission grounded on five main predictors, i.e., eosin Phil count, lung function, triadic inhaler remedy, former hospitalization, and neuromuscular complaint. It was set up that there's a high correlation between the 15280 VOLUME 10, 2022I. Mohamed et al. Machine Learning Algorithms for COPD Cases Readmission Prediction CORE score and COPD readmission, where a high CORE score meant a high threat of readmission and a short time to readmission. Unplanned readmission may be attributed to different reasons, similar to unseasonable discharge, limited social service support(34), complications associated with the former complaint, and regression of the original health condition(9). Other factors related to the cases themselves perhaps also be of great significance, similar to bad tone- care and drug problems(34),(9). Healthcare services may be measured by the position of unplanned readmission(21). Advanced rates of unplanned readmission indicate limited clinical operation, which will reveal its consequences in hospitals in the long run. In this study, we're aiming to understand threat factors related to admission and readmission of COPD cases in an Egyptian private sanitarium. Data has been collected from Al-Ghandoor Hospital(GH), Ash-Sharkia, Egypt. GH is considered the biggest private sanitarium in the megacity, furnishing further than 85 of the total health services for the megacity population. The exigency department is the first stop for COPD cases

with early symptoms. High-threat cases are also admitted to the sanitarium to admit applicable health services. In this study, all COPD admissions to GH from January 2019 to December 2019 are included. computation of unplanned readmission rates of COPD cases and related threat factors leading to this unplanned readmission are the two main objects of our study. We approached the problem from different aspects than was preliminarily done. originally, a conductive data collection phase was performed to gather accurate data that led to valid results. also, a multitude bracket algorithm(SVM with different Kernel functions) was applied. Two-time frames were used for the target class rather than a one-time frame. Our study could achieve the loftiest delicacy in prognosticating readmission with 91 ACC. This study was considered a foundation step toward erecting a largely accurate prophetic system.

5. EXISTING SYSTEM:

One of the most popular Machine Learning methods in the healthcare industry is predictive analytics. For instance, and have suggested the potential use of electronic health records as a foundation for healthcare analysis for smart health. Researchers have also used data mining and predictive analytics to stop the spread of chronic diseases. The majority of recent healthcare-related research has been on creating and putting into practice Machine Learning models to satisfy the unique and crucial needs of healthcare systems. The majority of this research concentrates on using large volumes of data to gain insightful knowledge about the present and future behavior of the system being studied.

6. PROPOSED SYSTEM:

In this project, we are utilizing the most powerful Machine Learning techniques such as Decision Trees (DT), Artificial Neural Networks (ANN), and Support Vector Machines (SVM) to develop classification models that can determine the targeted group of high-risk COPD patients who are most likely to be readmitted to the hospital within 30 days of their discharge. However, there is still an apparent lack of proof of their effectiveness. One of the

suggested causes of those studies' inefficiency may be attributed to their wasted work hunting the wrong targeted group of patients (i.e., patients with low risk of readmission). Therefore, there is a high need for reliable predictive models that are capable of accurately identifying high-risk patients most efficiently, allowing healthcare stakeholders to respond accordingly.

7. SYSTEM ARCHITECTURE:

Figure 7.1 shows a general perspective on the structure. The review utilizes an information-driven system to create models that can distinguish when patients with Chronic Obstructive Pulmonary Disease (COPD) should return to the emergency clinic. Utilizing strategies from ML, the review means to further develop well-being results by sorting out what makes individuals be readmitted. This strategy can further develop COPD patients' satisfaction by further developing how they are focused on and how their assets are utilized.

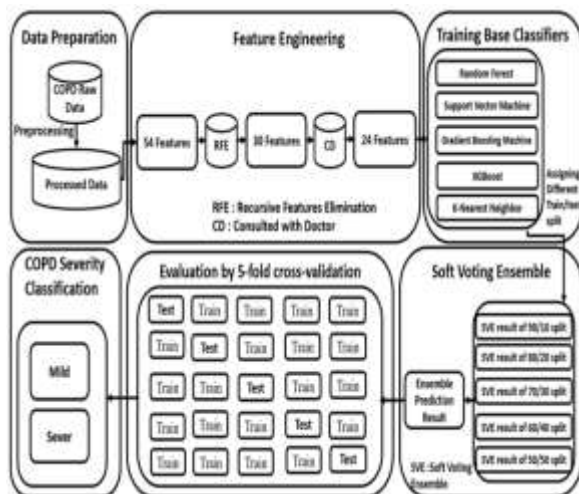


Figure 7.1. A complete architecture of study for COPD patients for identification of different stages.

8. ALGORITHM:

SUPPORT VECTOR MACHINE (SVM):

It's primarily used for classification, but it can also be adapted for regression. Here are the key concepts and

components of SVM: Support Vectors: SVMs work by finding the optimal hyperplane that best separates data into different classes. Support vectors are the data points closest to this hyperplane, and they play a crucial role in determining the position and orientation of the hyperplane. Hyperplane: In a binary classification problem (where you are classifying data into two classes), the hyperplane is the decision boundary that separates the two classes. It is chosen to maximize the margin between the classes, which is the distance between the hyperplane and the nearest data points from each class (support vectors). Margin: The margin is the space between the hyperplane and the support vectors. Maximizing the margin helps increase the robustness of the model, making it less prone to overfitting. Kernel Trick: SVMs can handle linearly separable as well as non-linearly separable data. The kernel trick is a mathematical transformation that maps the original data into a higher-dimensional space, making it easier to find a hyperplane that separates the data. C Parameter: This parameter controls the trade-off between maximizing the margin and minimizing classification errors. A smaller C value will prioritize a larger margin but may allow some misclassifications, while a larger C value will prioritize correct classifications but may lead to a smaller margin. Soft Margin SVM: In cases where the data is not perfectly separable, SVM can use a soft margin approach, allowing for some misclassification. The C parameter determines the balance between the margin width and the number of misclassifications allowed. The SVM algorithm aims to find the hyperplane that maximizes the margin while satisfying the constraint that all data points are correctly classified (or within the margin, in the case of soft margin SVMs). Steps in SVM training: Data Preprocessing: Normalize or scale your data to ensure that all features have the same scale. Choose a Kernel Function: Select an appropriate kernel function based on your data's characteristics. Parameter Tuning: Tune the model's parameters, such as the C parameter and kernel-specific parameters, using techniques like cross-validation. Training: The SVM algorithm finds the optimal hyperplane by solving a mathematical optimization problem. This process may involve the use of techniques like



quadratic programming. Prediction: Once the SVM is trained, you can use it to classify new data points by determining which side of the hyperplane they fall on. SVMs are known for their ability to handle high-dimensional data and their effectiveness in a wide range of applications, including image classification, text classification, and biological data analysis. However, they can be computationally expensive, especially with large datasets, and require careful parameter tuning.

Pseudo code for SVM algorithm:

```
# Import necessary libraries
from sklearn
import SVM
from sklearn.model_selection
import train_test_split
from sklearn.metrics
import accuracy_score,precision_score,
recall_score,f1_score
#Data Collection and preprocessing
Cargo your COPD case dataset and perform data
preprocessing way.
#Split the data into training and testing sets
X_test,y_train,y_test = train_test_split( features,
markers,test_size = 0.2,random_state = 42)
#Initialize the SVM classifier
clf = svm.SVC( kernel = ' direct', C = 1.0)
#Train the SVM model
clf.fit(X_train, y_train)
#Make prognostications on the test set
y_pred = clf.predict(X_test)
#estimate the model
delicacy = accuracy_score(y_test,y_pred)
perfection = precision_score(y_test,y_pred)
recall = recall_score(y_test,y_pred)
f1 = f1_score(y_test,y_pred)
#publish evaluation criteria
print( f" Accuracy{ delicacy}")
print( f" Precision{ perfection}")
print( f" Recall{ recall}")
print( f" F1 Score{ f1}")
#Optionally, you can save the trained model for
unborn use
#joblib.dump( clf,'svm_model. pkl')
```

In this pseudo-code:

- We import the necessary libraries, including scikit-learn's SVM classifier.

- We load and preprocess your COPD patient dataset (you'll need to replace features and labels with your actual data).
- We split the data into training and testing sets to evaluate the model's performance.
- We initialize an SVM classifier with a linear kernel and C parameter (you can tune these hyperparameters).
- We train the SVM model on the training data.
- We evaluate the model using common classification metrics such as accuracy, precision, recall, and F1-score.

9. SUMMARY:

It utilizes progressed information examination and ML to cause models to distinguish when individuals with Chronic Obstructive Pulmonary Disease (COPD) should return to the emergency clinic. The objective of the review is to figure out what makes individuals readmitted by checking out an enormous arrangement of patient information. This strategy can possibly work on understanding consideration and asset sharing by letting medical care laborers manage the things that make it more probable that a patient will be readmitted. The objective of the review is to work on the personal satisfaction of COPD patients by bringing down unnecessary emergency clinic readmissions through centered medicines and customized care plans in light of information-driven bits of knowledge.

10. RESULTS:

The results of the system are shown below.

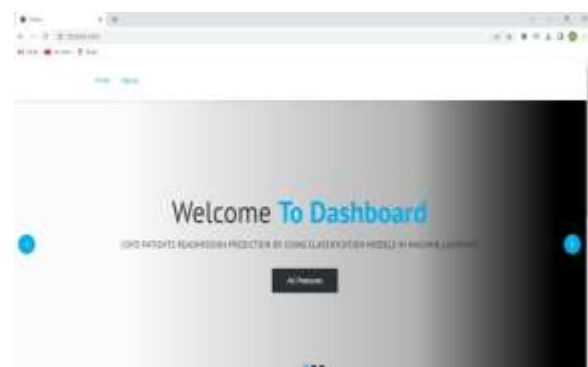
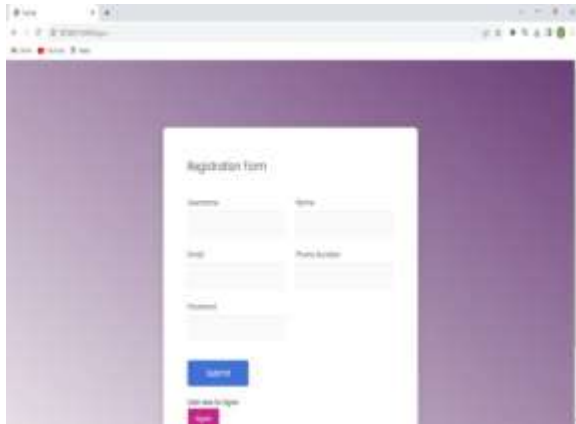


Fig 10.1 Home screen page

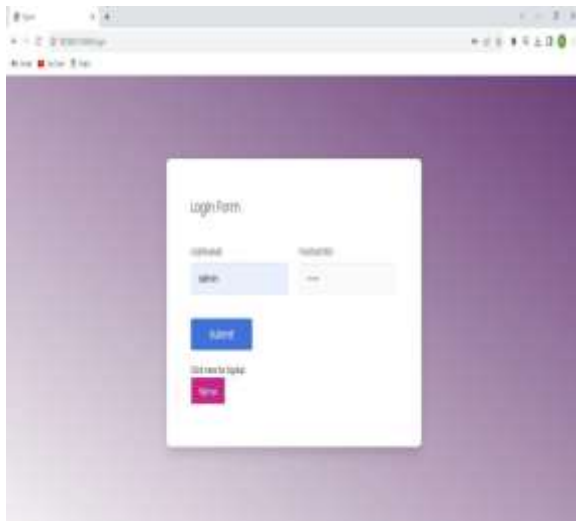


Figure 10.1 Shows the home page of COPD Readmission.



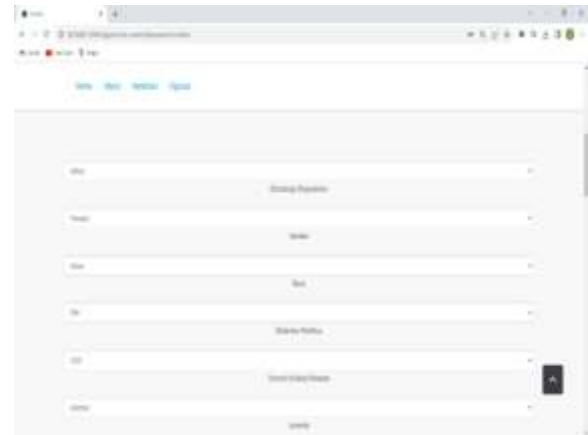
10.2 User registration

Figure 10.2 Shows the user information page where the username, password, phone number, etc., is displayed.



10.3 user login

Figure 10.3 Shows the user's login information for COPD readmission.



10.4 user input

Figure 10.4 Shows the patient's health-related information should be given as input.



10.5 prediction result

Figure 10.5 Shows the patient's information on whether should readmission or not in the hospital in a certain time.



11. FUTURE WORK:

Incorporate time series data analysis to account for changes in patient health over time, allowing for dynamic risk assessment. Develop patient-specific Prediction models that consider individual medical histories, genetics, and responses to treatment. Utilize Data from wearable devices and remote monitoring Systems to enhance predictions with real-time physiological data. Combine structured electronic health record (EHR) data with unstructured clinical notes, radiology reports, and other forms of healthcare data using natural language processing(NLP). Implement a real-time alert system that notifies healthcare providers when a patient's readmission risk increases significantly. Create a comprehensive dashboard for healthcare professionals, offering visualizations and trend analysis of readmission risk factors. Ensure compatibility with industry standards such as FHIR (Fast Healthcare Interoperability Resources) for seamless HER integration. Collaborate with multiple healthcare institutions to create a larger, more diverse dataset and improve model generalization.12 Develop patient education materials based on predicted risk factors to help patients understand how to manage their conditions. Integrate the model with telemedicine platforms to facilitate remote patient monitoring and virtual consultations. Enhance the model's interpretability by providing detailed explanations for predictions to healthcare providers. Create a patients facing mobile app that allows individuals to track their health-2'123, receive reminders, and access personalized recommendations. Develop ethical guidelines and mechanisms for responsible use of patient data and model predictions, ensuring privacy and compliance with regulations. Implement optimization algorithms to assist healthcare facilities in resource allocation, ensuring that interventions are allocated efficiently. Adapt the project for use in various healthcare systems worldwide, considering cultural and regional differences in COPD management. Collaborate with research institutions to conduct clinical trials to validate the model's effectiveness in real-world scenarios. Enable healthcare providers to directly prescribe recommended treatments and interventions

from within the system. Develop strategies to handle imbalanced data, as COPD readmission rates may vary significantly. Combine predictions from multiple classification models or different data sources to enhance overall accuracy. Extend prediction horizons to assess readmission risks beyond the immediate post- discharge period.

12. CONCLUSION:

Our principal expansion is utilizing clinical vector dispersing and ML to take care of the issue of class befuddle. This permits us to get around the issues with ordinary readmission foreseeing models and make expectations that are more exact. To anticipate medical clinic readmissions, we see how well unique ML frameworks can make forecasts. Independence and a restricted pay make it difficult for us to work really hard of judging. It was additionally difficult to Assemble a gathering of specialists who could zero in on our testing needs (like social occasion data, cleaning, and preparing). The way that just 195 COPD patient records were utilized in our review was another enormous issue. Later on, we will investigate various ways of organizing things to further develop the request plan. We likewise need to take a gander at more precise quantities of center readmissions since they will beggarly affect arranging and making post release models that function admirably. For instance, it is fascinating to sort out how likely it is that a patient will be readmitted inside a specific measure of time and investigate how prior confirmations might have changed this chance.

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